

Direct and cross-scheme effects in a research and development subsidy program

**Hanna Hottenrott, Cindy Lopes-Bento
and Reinhilde Veugelers**



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Hanna Hottenrott ^{a,b,c}, Cindy Lopes-Bento ^{b,c,d} and Reinhilde Veugelers ^{b,e}

a) Düsseldorf Institute for Competition Economics (DICE)

b) K.U.Leuven, Dept. of Managerial Economics, Strategy and Innovation, Leuven

c) Centre for European Economic Research (ZEW), Mannheim

d) University of Zurich, Zurich

e) Bruegel, Brussels

July 2014

Abstract

This study investigates the effects of an R&D subsidy scheme on participating firms' net R&D investment. Making use of a specific policy design in Belgium that explicitly distinguishes between research and development grants, we estimate direct and cross-scheme effects on research versus development intensities in recipients firms. We find positive direct effects from research (development) subsidies on net research (development) spending. This direct effect is larger for research grants than for development grants. We also find cross-scheme effects that may arise due to complementarity between research and development activities. Finally, we find that the magnitude of the treatment effects depends on firm size and age and that there is a minimum effective grant size, especially for research projects. The results support the view that public subsidies induce higher additional investment particularly in research where market failures are larger, even when the subsidies are targeting development.

Keywords: R&D, Complementarity, Research Subsidies, Development Subsidies, Innovation Policy

JEL-Classification: H23, O31, O38

Contact details:

Hanna Hottenrott, Düsseldorf Institute for Competition Economics (DICE), Heinrich Heine University Düsseldorf, Universitätsstrasse 1, 40225 Düsseldorf, Germany. hottenrott@dice.hhu.de

Cindy Lopes-Bento, K.U.Leuven, Department of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000 Leuven, Belgium. cindy.lopesbento@kuleuven.be

Reinhilde Veugelers, K.U.Leuven, Department of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000 Leuven, Belgium. reinhilde.veugelers@kuleuven.be

***Acknowledgements:** The authors are thankful to seminar participants at KU Leuven, the 5th ZEW/MaCCI Conference on Economics of Innovation and Patenting, the CONCORDi2013 Conference in Sevilla, the 2014 IIOC in Chicago for useful comments, especially Saul Lach and Pilar Benito. Lopes-Bento gratefully acknowledges financial support by the National Research Fund, Luxembourg, cofounded under the Marie Curie Actions of the European Commission (FP7-COFUND). Veugelers acknowledges support from FWO (G.0825.12) and KU Leuven (GOA/12/003). The authors thank IWT for providing the subsidy data and to the Centre for R&D Monitoring (ECOOM) for access to the R&D Survey data

1. Introduction

By now, a wide literature has investigated the effects of public subsidies on private R&D. Although this literature provides substantial evidence that subsidies are an effective tool to trigger additional R&D in the private sector¹, it is an open question at which stage of the R&D process such policy is most effective. R&D grants affect two related, but distinct activities, namely research ('R') and development ('D'). Research activities show fundamentally different characteristics from development activities, as research typically relates to more tacit knowledge, higher intangibility, higher outcome uncertainty and further market distance. These different characteristics may also explain different financing constraints, which are more binding for research than for development projects (Czarnitzki et al. 2011). As research typically involves early-stage activities with a wider set of possible applications, lower appropriability, and hence, higher knowledge spillovers, higher social returns are usually attributed to research than to development activities. These expected social returns related to research are usually used to make a bigger case for subsidizing research compared to development projects.

Previous studies on the impact of R&D subsidies generally do not distinguish between research and development. Partly, this is due to a lack of access to information on the nature of the project for which the subsidy was received as well as on how much private money firms spend on each of these activities. A study on Norwegian innovation policy by Clausen (2009) constitutes an exception. Clausen applies a taxonomy that distinguishes between projects that are "close to the market" and projects that are "far from the market". The author finds that while subsidies received for projects far from the market stimulate additional research spending, subsidies received for projects close to the market rather substitute firms' own spending on development. These results suggest that the extent to which public co-funding of R&D projects induces additional investments depends on the type of project. However, this study's classification of R&D subsidies is based on a taxonomy defined by the author, not by the policy design of the program under review.

¹ See for instance Hall and Maffioli (2008) who examine the literature on crowding-out effects since 2000. They find that most studies reject the null hypothesis of total crowding out of private R&D investments, with the exception of Wallsten (2000), analyzing the SBIR program in the United States who found dollar per dollar crowding-out effects. For recent studies on the effect of subsidies in Flanders, see for instance Czarnitzki and Lopes-Bento (2013) and Hottenrott and Lopes-Bento (2014).

The analysis presented in this paper investigates a project-based innovation policy implemented in the Belgian region of Flanders, which explicitly provides different schemes for research projects and development projects. Using data on all publicly co-financed projects, we are able to match the subsidy information with survey data that includes information on firms' own investment split in research and development. We study the period 2000 to 2009 in which during the first five years mainly mixed projects had been co-funded, while more recently, the policy has shifted to mainly support research and development projects separately. This unique dataset allows us to study direct as well as cross-scheme effects of such a targeted subsidy program.

Our analysis contributes to the existing literature in several ways. First, the ability to distinguish research from development grants allows us to assess the direct effects from research grants on research expenditures and from development grants on development expenditures. Second, we measure cross-scheme effects, assessing whether we find evidence for effects from research (development) grants on development (research) expenditures. Third, as we have information on the amount of subsidies received, both own as well as cross effects are measured on “net” expenditures. That means that our analysis not only detects evidence for full crowding-out as done primarily in the literature, but we can also draw conclusions on partial crowding out. Furthermore, we are able to estimate dose response functions that allow drawing conclusions on the elasticity of private R and D investments to public support depending on grant size. Finally, we investigate the heterogeneity in direct and cross additionality effects across recipient firms.

The results from a series of treatment effects models show that research subsidies induce additional net private research expenditures. In addition, research subsidies also generate significant positive cross-effects on development expenditures. For development subsidies, the direct effect on net private development investment is weaker, but we do find that development grants trigger significant additional research spending. While we find the elasticity of R and D to be positive for the mean amount of public money received, we find – especially for research grants – that the elasticity varies with grant size. Moreover, we find heterogeneity in the size of the treatment effect depending on firm size and age.

The paper proceeds as follows: Section 2 and 3 briefly describes the policy under review and the distinction between R and D schemes and present our hypotheses. Section 4 sets out the econometric framework and the data. Section 5 presents the results and section 6 concludes.

2. The policy design - Why distinct subsidy schemes?

R&D projects comprise different types of activities. Basic research primarily aims at acquiring new knowledge not necessarily with its application in mind, while applied research is an activity directed towards a specific application objective. Development draws from existing research results and aims at the creation and implementation of new and improved products and processes. Following the definition of the OECD Frascati Manual, research projects can be characterized by a high degree of outcome uncertainty and by being ‘far from the market’ without targeting commercialization opportunities directly. Research projects, however, create the foundations for future development projects (see e.g. Mansfield et al. 1971). Because research involves early stage technologies, the new knowledge is often tacit and therefore more difficult to fully appropriate by the creator of the knowledge (Arrow, 1962; Usher, 1964). Thus, economic theory suggests that the difference between social rates of returns and private ones is larger for research activities because of higher spillovers and hence, lower appropriability. Development projects, on the contrary, aim at commercializing inventions. As the development trajectory is more focused and often more incremental, it is less prone to spillovers when compared to research. Development outcomes may also be more tangible if firms protect their “close to the market”- innovations through formal and informal IP strategies (Cassiman and Veugelers, 2002). Because development projects are closer to the actual implementation of an invention or the introduction of a new product to the market, firms may appropriate the returns more easily.

Beyond differences in spillovers and appropriability, research and development activities are different in their risk and uncertainty profile. Karlsson et al. (2004) promote the idea that research is a more discontinuous process, which may or may not result in solutions whereas development is a more continuous search for solutions to an existing set of ideas. Such differences in risk and uncertainty translate into different sensitivities of research versus development investments to imperfections in the financial markets. Czarnitzki et al. (2011) find for a sample of Flemish firms that research investments are much more dependent on firms’ internal financial resources compared to development projects.

Given this heterogeneity of activities within the R&D process, it seems reasonable for policy makers to consider these specificities when designing innovation policy tools. With higher spillovers, more difficult appropriation and constrained access to external finance for research activities, the market failures for research is likely to be larger than for development activities.

Research projects may therefore justify a higher subsidy rate, i.e. the share of total project costs covered by the grant. Moreover, a distinct scheme may allow applying different selection criteria for research projects than for development projects, taking the specificities of research in terms of risk, duration and expected outcomes into account.

The Flemish R and D policy

Flanders, like many industrialized economies, has project-based R&D subsidy programs in place. The Flemish funding agency (IWT), an independent government body, administers the permanently open and non-thematic R&D subsidy scheme. Any firm located in Flanders may submit a project in any technological field at any time of the year. An external board of referees evaluates the applications and decides whether the project is eligible for funding.

Over the past decade, the Flemish innovation policy moved its focus towards distinct grants for ‘R’ and ‘D’ projects that do not only differ in terms of the projects’ focus, but also with respect to the share in total project costs borne by the funding agency. The share of cost covered by the government varies for industrial ‘basic and strategic’ research, ‘experimental development, and prototyping’ and so-called ‘mixed projects’. For research projects, the base rate is about 50% and it is 25% for development. In both schemes, an additional 10% may be granted to medium sized firms and an extra 20% to small firms. Collaborative projects may receive another additional 10%. The minimum project size is one hundred thousand euros and the subsidy is capped at 3 million euros per project.²

As can be seen in Figure 1, since 1997 an increasing number of firms participated in the Flemish subsidy scheme and the total amount of funding more than doubled during this period. From 1997 to 2009, the Flemish government co-funded a total number of 2,872 projects in 1,868 different firms. While the average size of the government’s contribution per project remained rather constant over time, the overall number of co-funded projects doubled. Table 1 summarizes the key characteristics of the subsidy-schemes for the funding periods 1997-2009. These numbers are at the annualized project (not firm) level and the amounts refer to the government’s share in

² See <http://www.iwt.be/english/funding/subsidy/industrial-projects>.

total project costs. Among subsidized firms, each firm has on average 1.4 running projects in a given year and receives a payment of 175 thousand euros (median = 53).

Figures 1 and 2: Evolution of participation in the subsidy program and grants by type of scheme at the project level (amounts in T Euros)

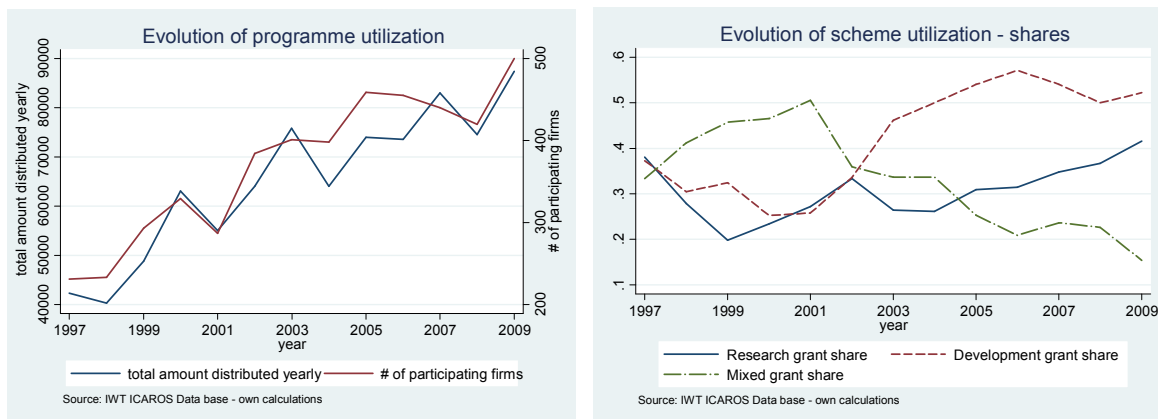


Table 1: Co-financed R&D projects in the Flemish innovation policy design 1997 -2009 (4,827 obs.)

	<i>mean</i>	<i>std. dev.</i>	<i>min</i>	<i>max</i>
Projects per firm	1.420	1.514	1	24
Research grant (amt. yearly)	32.647	172.977	0	6,360.925
Development grant (amt. yearly)	49.425	204.339	0	6,706.612
Mixed grant (amt. yearly)	90.353	382.030	0	7,526.763
Average yearly amount	175.149	578.673	0	14,637.96

Note: Share among all granted projects. Source: IWT ICAROS data base. Yearly amount in thousand Euros and at the project-year level.

As can be gathered from Figure 2, the dominating tendency of the Flemish funding agency moved away from mixed R&D projects for which no clear priorities on the stage of the R&D process are set *a-priori* towards specific programs (i.e. either R or D). Indeed, while the yearly amount spent by project did not change over the years, as shown by Figure 2, one can see that until the early 2000's mixed projects accounted for the lion's share among all grants. By 2005 mixed projects had been overtaken by pure development grants and by pure research grants in terms of

their share in total granted projects. With this shift towards a more targeted approach, it is interesting to study to what extent a research or development grant triggers additional research and development investments by the recipient firms, whether there are differences in terms of efficacy between both schemes and whether there are any cross scheme effects.

3. Direct and cross additionality effects from R and D subsidies on R and D expenditures

Based on previous findings that have repeatedly shown positive additionality of R&D subsidies on R&D spending in Flanders (see eg Czarnitzki and Lopes-Bento (2013) and Hottenrott and Lopes-Bento (2014)), we expect to also find positive own additionality from R and D grants.

H1: The direct effects from research subsidies on research expenditures are positive.

H2: The direct effects from development subsidies on development expenditures are positive.

Based on the arguments in section two, as research investments may be more constrained compared to development investments, we expect the direct effects of a research grant to be larger than the direct effect of a development grant leading to

H3: The direct effects from research subsidies on research expenditures are larger than the direct effects of development grants on development spending.

In addition to direct effects, there might also be cross-effects across schemes. That is, recipients of research (development) grants may also invest more in development (research) in response to the subsidy. The reasoning that leads us to expect positive cross effects starts from the premise that research and development activities influence the expected returns to innovation differently. The productivity of knowledge, i.e. a firm's effective knowledge base, creating innovative products and processes, results from the interaction between research and development activities. Development is specific to the firm's business and, hence, necessary to develop an effective knowledge base that serves to improve the firm's position. Research on the other hand serves to improve the efficiency of development. In order to better understand how to conduct development, firms need to do research. Quoting Rosenberg (1990): "A basic research capability is essential for evaluating the outcome of much applied research for perceiving its possible implications..."

Therefore, research can be regarded to be complementary to development. Several explanations as to the exact mechanisms for establishing a complementary relationship between research and development have been suggested in the literature (Nelson; 1959; Evenson and Kislev, 1975; Cassiman et al., 2002). As research provides a codified form of problem-solving, it can increase the efficiency of development activities (Arrow, 1962). In addition, research know-how serves as a map for technological landscapes guiding development in the direction of most promising technological venues avoiding thereby wasteful experimentation (Fleming and Sorenson, 2004). A better and more fundamental understanding of the technology landscape encourages non-local search for improving technologies as opposed to local search, leading to the exploration of more diverse development projects. In addition, research know-how leads to a better identification, absorption and integration of external (public) knowledge (Cohen and Levinthal, 1989; Gambardella, 1995; Cockburn and Henderson, 1998; Cassiman and Veugelers, 2006). Faster identification, absorption, and integration of external knowledge in turn lead to increased productivity of the development process (Fabrizio, 2009; Cassiman et al., 2008).

Although in the short run, research and development activities can be seen as substitutes competing for available fixed resources, in the long-run when resources are not fixed, research and development activities complement each other as outlined above. When research and development activities are complementary, the marginal returns of research increase with higher spending on development and vice versa. A consequence of a complementary relationship between research and development activities is that the cross effects from subsidies are positive, i.e. a higher subsidy for research will not only stimulate research expenditures, but also, because of the induced higher marginal returns from development with higher research expenditures, research subsidies will also stimulate development expenditures and vice versa: development subsidies will also increase the marginal returns from research and therefore stimulate research expenditures. Firms that are more efficient in doing research, are more likely to have bigger cross effects, to such an extent that research subsidies could be even more powerful instruments to stimulate development than development subsidies.

In line with the above reasoning, we further hypothesize that

H4: The cross effects from research subsidies on development expenditures are positive and the cross effects from development subsidies on research expenditures are positive.

4. Empirical strategy

The analysis of direct and cross additionality is pursued in three steps. First, we estimate direct average treatment effects as well as cross-scheme average treatment effects using a nearest-neighbor propensity score matching procedure. IV regressions serve as robustness check taking potential selection on unobservables into account. Second, we make use of the detailed information on the size of the individual grants to estimate the impact of different levels of treatment, employing a generalized propensity score (GPS) method to estimate dose response functions (DRF). Finally, we try to disentangle the factors driving the direct and/or cross effects by analyzing the heterogeneity of these effects in light of relevant firm characteristics.

a) Treatment effects estimation

The average treatment effect on the treated is estimated by the econometric matching estimator. The econometric matching estimator directly addresses the question of “How much would a treated firm have invested in R or D if it had not received a subsidy?” Given that the counterfactual situation is not observable, it has to be approximated through an estimation procedure. In order to do so, we employ a nearest neighbor propensity score matching. That is, we pair each subsidy recipient with a non-recipient firm by choosing nearest “twins” based on their similarity in the estimated probability of receiving such a subsidy. The estimated probability stems from a probit estimation on binary variables indicating the receipt of a subsidy S_r or S_d , controlling for any observable characteristics able to drive the selection into the respective funding scheme. This setting thus allows us to take into account that subsidies (as well as the different type of grant) are not randomly distributed, but are subject to selection. Looking for the single most similar firm, the matching estimator accounts for this selection, and after having paired each treated firm with the most similar non treated firm, we can assume that any remaining differences can be attributed to the policy effect. In addition to the similarity in the propensity score, we further require firms in the selected control group to belong to the same industry and to be observed in the same year as the firms in the treatment group.³

In order for the matching estimator to be valid, the conditional independence assumption (CIA) has to hold (Rubin, 1977). In other words, in order to overcome the selection problem,

³ For the detailed matching protocol, see Table A.1 in Appendix 1.

participation and potential outcome have to be independent for individuals with the same set of exogenous characteristics X . Thus, the critical assumption using the matching approach is to observe all factors determining the entry into the program. If this assumption holds, the average treatment effect on the treated firms can be represented as follows:

$$\alpha^{TT} = \frac{1}{N^T} \sum_{i=1}^{N^T} (Y_i^T - \hat{Y}_i^C) \quad (1)$$

where Y_i^T indicates the outcome of treated firms and \hat{Y}_i^C the counterfactual situation, i.e. the potential outcome which would have been realized if the treatment group ($S=1$) had not been treated. In other words, for the untreated firms, \hat{Y}_i^C corresponds to their internal R&D expenditures. $S \in \{0,1\}$ indicates the receipt of a subsidy and N^T the number of treated firms.

Given that we have several treatments, we will estimate different treatment effects. More precisely, we distinguish five treatment effects:

- (i) the effect from any subsidy received on overall R&D expenditures (this treatment comprises all subsidy types: mixed, research and development grants provided by the Flemish funding agency),
- (ii) the direct effect from an ‘R’ grant on ‘R’ expenditures,
- (iii) the cross effect from an ‘R’ grant on ‘D’ expenditures,
- (iv) the cross effect from a ‘D’ grant on ‘R’ expenditures
- (v) the direct effect from a ‘D’ grant on ‘D’ expenditures.

$$\text{i. } \alpha^{TT_any_R\&D} = \frac{1}{N^{T_R\&D}} \sum_{i=1}^{N=T} (Y_i^{T_R\&D} - \hat{Y}_i^C) \quad (2)$$

$$\text{ii. } \alpha^{TT_Sr_R} = \frac{1}{N^{T_R}} \sum_{i=1}^{N=T} (Y_i^{T_R} - \hat{Y}_i^C) \quad (3)$$

$$\text{iii. } \alpha^{TT_Sr_D} = \frac{1}{N^{T_R}} \sum_{i=1}^{N=T} (Y_i^{T_D} - \hat{Y}_i^C) \quad (4)$$

$$\text{iv. } \alpha^{TT_Sd_R} = \frac{1}{N^{T_D}} \sum_{i=1}^{N=T} (Y_i^{T_D} - \hat{Y}_i^C) \quad (5)$$

$$\text{v. } \alpha^{TT_Sd_D} = \frac{1}{N^{T_D}} \sum_{i=1}^{N=T} (Y_i^{T_R} - \hat{Y}_i^C) \quad (6)$$

It is important to note that the control group is always adapted to the treatment. That is, we always define the control group in such a way that it is exclusively composed of *unsubsidized* firms. Concretely, this means that if we consider research as a treatment effect, for instance, we drop

firms that have received a development grant, a mixed grant or a grant from any other (Belgian or non-Belgian) funding agency from the control group.

b) Impact of the amount of the treatment

In a second step, we incorporate the level of subsidies in a treatment effects analysis using a generalized propensity score to estimate a dose response function. While most evaluation studies on R&D subsidies limit themselves to estimating the average treatment effect based on a binary treatment variable, we take the grant size, i.e. the amount distributed via the subsidy scheme, into account. We follow Hirano and Imbens (2004) who developed a generalization of the propensity score matching for the case of continuous treatments. The generalized propensity score (GPS) is defined as

$$GPS = r(T, X) \quad (7)$$

with T_i being the treatment level and X_i a vector of pretreatment covariates. Thus, the GPS can be estimated as in the binary treatment case by maximum likelihood (ML) estimation. We can then model the conditional expected outcome and derive the treatment-specific dose response function (DRF) on net research and net development expenditures as a function of T and GPS .⁴

$$\begin{aligned} \phi[E(Y_i | T_i, GPS_i)] &= \psi(T_i, GPS_i; \alpha) \\ &= \alpha_0 + \alpha_1 \cdot T_i + \alpha_2 \cdot T_i^2 + \alpha_3 \cdot T_i \cdot GPS_i \end{aligned} \quad (8)$$

For obtaining the DRF, we average the estimated conditional expectation $\beta(t, r) = E(Y | T = t, GPS = r)$ over the GPS for all levels of the treatment distribution⁵:

$$\mu(t) = E[\beta(t, r(t, X))] \quad (9)$$

c) Heterogeneity of the direct and cross effects across firms

Finally, we study the individually estimated treatment effects to explore the heterogeneity of treatment effects across firms. In order to do so, we derive the estimated treatment effects α_i^{*TT} at the firm level as:

$$\alpha_i^{TT*} = Y_i - \hat{Y}_i^c \quad (10)$$

⁴ See Bia and Mattei (2008) for the technical details and Bia et al. (2011) for an application to R&D subsidies.

⁵ Note that we bootstrap standard errors in this step with 200 replications.

This individual treatment effect is simply the deviation of the treated firms' net expenditures on research or development from those of its matched twin. Based on this individual effect, we analyze whether certain firm characteristics explain direct and / or cross effects.

Data

The public funding information has been provided by the funding agency IWT and contains detailed information on the duration of the project, the total amount received and the type of subsidy scheme under which the subsidy had been granted.

The data on firms' research and development expenditures stem from the Flemish part of the OECD R&D survey. This survey composes the Main Science and Technology Indicators across OECD countries. In Flanders, the R&D survey draws from a permanent inventory of all R&D-active firms. The OECD survey asks firms to split their total R&D expenditures into their R and D components. A guideline for respondents on how to attribute activities to R and D is provided by examples and definitions based on the Frascati manual. Beyond the budgets for R and D, the survey also contains rich information on other firm characteristics, like R&D employees, the group and ownership structure, subsidies from sources outside Flanders, and R&D collaborations.

We combine the survey data and the funding information based on the firms' unique VAT numbers. Our analysis makes use of five consecutive waves of the bi-annual survey covering the period from 2000 to 2009 and it comprises R&D-active firms from manufacturing and business-related service sectors.

We complemented the repeated cross-sectional survey data with patent statistics issued by the European Patent Office (EPO). The "EPO/OECD patent citations database" covers all patents applied for at the EPO since its foundation in 1978 as well as all patents applied for under the Patent Cooperation Treaty (PCT) in which the EPO is designated, so-called "Euro-PCT applications". Data from the Belgian patent office serves as information about patents filed in Belgium only. Patent information is available as a time series from 1978 onward and has been collected by using text field search. We checked all potential hits of the text field search engine manually before merging it to the firm-level survey data. Finally, we collected the firms' balance sheet information, in particular the firms' tangible assets, from the Belfirst data base provided by Bureau van Dijk.

After the elimination of incomplete records, the final sample contains a total number of 4,442 firm-year observations corresponding to 1,252 different firms. About 20% of these firms have benefitted from some type of IWT subsidy. Roughly five percent of the firms have reported the receipt of a subsidy from another funding source, such as the federal government or the EU during that time. Table 2 presents some descriptive statistics in terms of the grant distribution. While about 9% of the firms of our sample benefitted from a development grant during the period under review, only 5.5% received a research grant. When considering exclusively subsidized firms, we see that on average 27% of the firms benefitted from a research grant, as compared to 44% receiving a development grant. In terms of grant size, the average annualized amount for a development grant among the recipient firms is close to 54 thousand Euros compared to 37 thousand Euros for a research grant. As firms may hold multiple grants, the overall annualized amount is about 230 thousand among the grant recipients. The median is lower with about 83 thousand Euros in a given year.

Table 2: Within sample grant characteristics

Variable	Median	Mean	Std. Dev.	Min	Max
<i>Grant types all firms (N = 4442)</i>					
Any-grant	0	0.201	0.401	0	1
Research grant	0	0.055	0.228	0	1
Development grant	0	0.090	0.286	0	1
<i>Grant types of subsidy recipients (N = 893)</i>					
Research grant	0	0.274	0.446	0	1
Development grant	0	0.448	0.498	0	1
Research grant (annual amount)	0	37.218	161.927	0	1940.826
Development grant (annual amount)	0	54.040	133.591	0	1558.176
Total amount yearly	82.959	230.253	501.666	0.938	4787.638

Note: amounts in thousands of Euros. Total grant size distributed over grant duration.

Research and Development investment variables

The outcome variables in the treatment effect estimation are firms' R&D (as well as R and D) intensity, which are the ratios of R&D (respectively R and D) to sales, multiplied by 100. The total annual R and D expenditures are taken directly from the survey after the survey data been systematically checked for plausibility and consistency. As we have information on the subsidy

amounts received, we have constructed our outcome variables as *net* amounts of R and D spending. That is, we have deducted the annualized amount of the subsidy from the firms' total R and D expenditures. We distributed the full amount of the grant equally over the years of duration of the project. For the baseline model, the subsidies of the mixed-scheme have been deducted 50% from 'R' investment and 50% from 'D' investment.⁶

Probability to receive subsidies

We model the receipt of a subsidy by a dummy variable equal to one if a firm received financial support, zero otherwise. This yields three main explanatory variables: the receipt of any subsidy (*SUB*), a research project grant (*S_r*) and a development project grant (*S_d*).

We control for other characteristics, likely to influence the receipt of either one of our two policy treatments. The number of employees takes into account possible size effects. Given that this variable is skewed, it enters the model as a natural logarithm (*lnEMPL*). We also allow for a potential non-linear relationship by including (*lnEMPL²*). We further include a dummy variable that is equal to one if a firm qualifies as a SME (*SME*). Belgian SMEs are eligible for a higher subsidy rate than large-size firms, which may impact the likelihood of applying for, and hence, receiving a subsidy.⁷ The higher subsidy rate for SMEs can be received for any funding scheme and no difference is made between R or D projects.

In addition, we include a dummy variable capturing whether or not a firm is part of an enterprise group with a foreign parent company (*GP_FOREIGN*). It is a-priori not clear whether belonging to a group with a foreign parent has a positive or negative influence in the receipt of a subsidy by the Flemish funding agency. Firms that belong to a group with a parent located in a different country may be less likely to apply for a subsidy in Belgium than other firms. In addition, firms having a large majority shareholder do not qualify for the Belgian SME programs in which

⁶Co-funded mixed projects are included in the treatment for "any scheme". Given that we are mainly interested in the direct and cross effects of the research and the development grant schemes, we do not undertake a separate analysis for the mixed grant scheme. In order to perform our analyses on the net amount of our outcome variables, we do deduct the amounts of the mixed scheme grants from R&D (respectively 'R' and 'D') intensity. This ensures that our outcome variables are net of any type of grant and that we really only consider private investment in our outcome measures.

Since we cannot be sure about the exact distribution of this scheme for both components, we re-estimated our findings using a 30/60 respectively 60/30 distribution as a robustness check (results are presented in Tables A.4 and A.5 of Appendix 3).

⁷ SME follows the definition of the European Commission, according to which an SME should have less than 250 employees and has either sales less than 50 million euros (or a balance sheet total of less than 43 million euros).

higher subsidy rates are attributed to recipient firms, giving them less incentives to apply. On the other hand, firms with a foreign parent company might enjoy a larger network and be better able to incur the application costs.

The log of the firm's age ($\ln AGE$) is included in the analysis as older firms may have more experience than younger firms reducing their application costs. On the other hand, young firms are more likely to be financially constrained than older or more established firms are, and might therefore be more likely to apply for public support. Similar as for size, we allow for a non-linear relationship by included $\ln AGE^2$.

We further control for whether a firm collaborated for its R&D activities (CO). Given the Belgian funding agency encourages firms to collaborate for the R&D activities (for both, R and D programs), being a collaborator may be an important determinant in receiving, and applying for, public support.

R&D experience, especially if successful, may increase firms likelihood to apply again and to be granted a public subsidy. To capture these dynamics, we include the firms' past patent stock in our regression. Patent stocks (PS) are computed as a time series of patent applications with a 15% rate of obsolescence of knowledge capital, as is common in the literature (see e.g. Griliches and Mairesse, 1984; Jaffe, 1986):

$$PS_{i,t} = (1 - \delta)PS_{i,t-1} + PATAPPL_{i,t} \quad (11)$$

where $PATAPPL$ is the number of patent applications in each year. The patent stock enters into the regression as patent stock per employee to avoid potential multicollinearity with firm size (PS/EMP). Just as past successful R&D projects might play an important role for the application and granting of a subsidy, experience with a specific funding scheme might drive the selection process. In order to consider this, we construct a dummy variable capturing if a firm had a subsidized project in the previous three years in any funding scheme.

In addition, we include firms' capital intensity in order to control for differences in the technologies used in the production process. Companies having a more capital-intensive production might rely more heavily on R&D than labour-intensive firms.

Finally, sixteen industry dummies are included to control for unobserved heterogeneity and technological opportunity or appropriation across sectors (See Table A.2 of Appendix 2 for the distribution of firms across industries). Ten time dummies are included to capture macroeconomic shocks and changes in the policy design over years.

Descriptive statistics

Table 3 shows the descriptive statistics of the variables of interest distinguishing between subsidized and non-subsidized firms. The latter serve as control group in our empirical analysis as these firms did not receive any grants, neither from the Flemish funding agency nor from any other funding source like for instance the national government or the European Union.⁸

Subsidized firms, no matter which type of support they receive, have on average a higher net R&D intensity and this for both stages of R&D: research intensity as well as development intensity. Comparing the R versus D grant recipients reveals that the research grant-receiving firms have larger development intensities. This is already reminiscent of the complementary role research plays with regard to development.

With respect to the control variables, we see that, on average, subsidized firms are significantly larger compared to non-subsidized firms. Likewise, subsidized firms have a significantly higher patent stock per employee and have received more often subsidies in previous years. Subsidized firms (irrespective of the scheme) further engage significantly more often in R&D collaboration. Comparing research and development grants recipients, we see that firms benefitting from research grants have on average a higher patent stock per employee and more experience with the research support scheme.

⁸ The information on funding sources other than IWT is obtained from the survey. Firms are explicitly asked to indicate regional, national and supranational funding sources for supported R&D projects.

Table 3: Detailed descriptive statistics by subsidy type

	I		II		III		IV		I vs. II	I vs. III	I vs. IV	III vs. IV
	Non-subsidized firms, N=3,549		Subsidized firms, any type [§] , N=893		'R' subsidized firms, N=245		'D' subsidized firms, N=400		P-values of two-sided t-tests on mean differences of the groups of interest			
Variables	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.				
Outcome variables												
<i>R&D_intensity_net</i>	0.064	0.152	0.149	0.246	0.176	0.269	0.147	0.247	p<0.000	p<0.000	p<0.000	p=0.162
<i>Development_intensity_net</i>	0.031	0.088	0.058	0.119	0.086	0.157	0.050	0.110	p<0.000	p<0.000	p=0.001	p<0.000
<i>Research_intensity_net</i>	0.033	0.102	0.091	0.187	0.089	0.181	0.097	0.194	p<0.000	p<0.000	p<0.000	p=0.568
Control variables												
<i>R&D cooperation</i>	0.319	0.466	0.702	0.458	0.686	0.465	0.650	0.478	p<0.000	p<0.000	p<0.000	p=0.192
<i>Patent stock per employee</i>	0.017	0.087	0.047	0.131	0.054	0.133	0.035	0.088	p<0.000	p<0.000	p<0.000	p=0.048
<i>Past research grants</i>	0.042	0.200	0.152	0.360	0.261	0.440	0.135	0.342	p<0.000	p<0.000	p<0.000	p<0.000
<i>Past development grants</i>	0.060	0.238	0.163	0.370	0.180	0.385	0.260	0.439	p<0.000	p<0.000	p<0.000	p=0.116
<i>Past mixed grants</i>	0.032	0.175	0.226	0.419	0.212	0.410	0.200	0.401	p<0.000	p<0.000	p<0.000	p=0.370
<i>Foreign group</i>	0.225	0.418	0.243	0.429	0.196	0.398	0.195	0.397	p=0.256	p=0.273	p=0.157	p=0.744
<i>SME</i>	0.841	0.366	0.738	0.440	0.808	0.395	0.770	0.421	p<0.000	p=0.210	p=0.001	p=0.531
<i>Employees</i>	147.687	320.687	323.804	757.329	259.959	616.656	290.134	686.021	p<0.000	p=0.005	p<0.000	p=0.782
<i>Capital intensity</i>	41.295	56.470	39.451	51.926	36.359	39.076	38.946	55.047	p=0.352	p=0.066	p=0.402	p=0.600
<i>Age</i>	24.606	18.089	23.460	21.699	21.657	21.465	22.985	21.262	p=0.146	p=0.037	p=0.143	p=0.870

Notes: §contains firms with mixed grants.

5. Empirical results

5.1. The matching results

Table 4 shows the results of the probit estimations on the likelihood to receive subsidies. This serves as basis for the propensity score matching. The first model predicts the probability of the receipt of any type of subsidy, ignoring the distinction between research grants and development grants. The second and third model differentiate between receiving a research and a development subsidy.

Table 4: Probit estimations on probability of receiving any grant, a research or a development grant

	Any type of subsidy N=4,442		Research subsidy N=4,338 [†]		Development subsidy N=4,442	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
<i>Patent stock per employee</i>	1.070***	0.226	0.642**	0.280	0.140	0.278
<i>Past research grants</i>	0.494***	0.089	0.710***	0.098	0.167	0.101
<i>Past development grants</i>	0.412***	0.081	0.270***	0.102	0.717***	0.083
<i>Past mixed grants</i>	0.833***	0.087	0.362***	0.109	0.350***	0.097
<i>Foreign group</i>	-0.015*	0.065	-0.158*	0.094	-0.306***	0.080
<i>R&D cooperation</i>	0.781***	0.050	0.445***	0.072	0.530***	0.060
<i>SME</i>	0.016	0.110	0.165	0.163	-0.018	0.132
<i>ln(Employees)</i>	0.025	0.073	-0.109	0.099	-0.010	0.084
<i>ln(Employees)²</i>	0.011	0.010	0.018	0.013	0.005	0.011
<i>Capital intensity</i>	0.029	0.023	0.032	0.033	0.006	0.027
<i>Age</i>	-0.423***	0.141	-0.043	0.196	-0.233	0.166
<i>(Age)²</i>	0.051	0.026	-0.016	0.037	0.023	0.031
LR chi ² (36)	917.49***		247.73***		364.95***	
Joint signif of industry dummies chi ² (15)	72.34***		17.05		40.17***	
Joint signif on time dummies chi ² (9)	32.83***		17.65**		38.09***	

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). All models contain a constant, industry and year dummies (not presented).

“Any type of subsidy” includes research subsidies, development subsidies and mixed grants.

[†] We lose 104 observations in the estimation on the probability of receiving a research grant, as no firm in the pulp and paper industry received such a grant.

As can be seen from Table 4, past research, development and mixed grants significantly determine current subsidy receipts for any type of subsidy. When disentangling research subsidies versus development subsidies, the incumbency effect is much stronger within programs, but there are also cross-scheme incumbency effects, particularly from past development scheme experience into current research subsidy receipts. In terms of past research experience, the patent stock per employee only displays a significant impact for research (or any type of) grants, but not for development ones, confirming patent stock as signal of quality/success is particularly important for the more risky and uncertain research activities. Being part of a group with a foreign parent displays a negative impact on the receipt of any type of grant. Past R&D collaboration is highly significant in driving the selection into any type of subsidy scheme, showing the importance attributed to collaboration by the funding agency. Finally, we do not find any evidence that size matters for the selection into the program. It should be noted though that while the size variables are individually not significant in driving the selection into receiving a grant, they are jointly significant in terms of receiving any type of subsidy ($\chi^2(3) = 38.10^{***}$). When disentangling between subsidy schemes, the size variables are also jointly insignificant ($\chi^2(3) = 2.77$ for research and $\chi^2(3) = 2.93$ for development respectively).

Table 5 presents the results of our matching estimation.⁹ We find positive additionality from any subsidy on all outcome variables of interest. This positive additionality from R&D grants on R&D (as well as ‘R’ and ‘D’) confirms previous findings. It is re-assuring to see that even though previous estimations were mainly based on gross amounts, we find similar results when using the net amounts. We can thus complement previous findings that rejected a total crowding-out by finding evidence allowing us to reject partial crowding-out. This is the case for the overall receipt of any subsidy as well as for the specific subsidy schemes.

To further analyze our predictions in terms of direct and cross effects, we present in Table 5 t-tests on mean difference between the average treatment effects across treatments. For research grants, we see a significant direct effect as well as a significant cross effect, and that both effects

⁹ In order to ensure a balanced matching for both subsidy schemes, we use the log of firm size as an additional matching criterion when estimating the effect of the development subsidy scheme. As explained in the previous section and found by previous theoretical papers, development is often done primarily by larger firms. This is also the case in our data, where development subsidies were predominantly received by larger firms. This had thus to be taken into account to make sure that adequate neighbors could be found for the estimation of our control group.

are of similar size (confirming Hypotheses 1 and 4). Indeed, as shown by the t-test, the difference is not statistically significant. In terms of the impact of development subsidies, the picture looks different. While there is also a direct as well as a cross effect. This confirms Hypotheses 2 and 4. Interestingly, the cross effect from D to R is significantly higher than the direct effect from D to D as shown by the t-test on mean difference.

Looking at the magnitude of the treatment effects, it turns out that in line with our Hypothesis 3, the direct effect from R to R (0.031 percentage point increase in research intensity) is larger than the direct effect from D to D (0.014 percentage points increase in development intensity).

When analyzing the impact of both subsidy types on research intensity, we see that the effect from a research grant on research expenditures (0.031) is lower than the impact triggered by the development grant (0.055). Based on the t-test on mean difference, we can conclude that this difference is not statistically significant though. Likewise, when comparing the impact of both types of grants on development intensity, we find that the difference is not statistically significant.

Table 5: Matching results¹⁰

	Outcome variables			T-test on mean difference			
	<i>Net R&D intensity</i>	<i>Net Research intensity</i>	<i>Net Development intensity</i>				
Treatment				I vs. II	III vs. IV	I vs. III	II vs. IV
Any subsidy (N=701)	0.062***	0.045***	0.017***				
Research subsidy (N=198)	0.070***	0.031** (I)	0.038*** (II)	p=0.733			
Development subsidy (N=319)	0.069***	0.055*** (III)	0.014* (IV)		p=0.006	p=0.214	p=0.131

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Only outcome variables are presented as control variables are all balanced after the matching.

¹⁰ As shown by the overall significance of the probit after the matching, the matching was balanced in all three cases. The test statistic reads as follows for the three cases under review: Wald $\chi^2(36) = 16.03$, Prob > $\chi^2 = 0.998$ for the case of any subsidy, Wald $\chi^2(35) = 9.95$, Prob > $\chi^2 = 1.00$ for the case of a research subsidy and Wald $\chi^2(36) = 18.72$ (Prob > $\chi^2 = 0.992$) for case of receiving a development grants.

In terms of the policy trend outlined in the previous section and as could be gathered from Figure 2, we observe a policy shift from supporting mixed projects towards targeted R and D support as of around 2005 onwards. When we compare the average treatment effect in the period prior 2005 to the one afterwards (Table 6), we indeed find that the average treatment resulting from any subsidy is higher under the targeted regime, i.e. with R and D grants rather than supporting mixed projects. In particular, we find an average treatment effect (ATT) equal to 0.044 for the period until 2004 and an average treatment effect (ATT) equal to 0.078 for the post-2005 period. The difference is statistically significant ($\Pr(T < t) = 0.042$). When we test which component of R&D had benefited from the policy shift, we find that research intensities increased more than development. Although we find both effects to be higher in the more recent period, the difference is only significant for research intensities.

Table 6: Matching results by period

Treatment	Outcome variables		
	<i>Net R&D intensity</i>	<i>Net Research intensity</i>	<i>Net Development intensity</i>
2000-2004			
Any subsidy	0.044***	0.030***	0.014
2005-2009			
Any subsidy	0.078***	0.058***	0.020***
<i>T-test on ATT difference</i>			
Pr(T<t)	0.042**	0.028**	0.310

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%).

5.2. Robustness check: Potential selection on unobservables

Given that the matching estimator only controls for the selection on observables, we test whether the main conclusions change if we account for a potential selection on unobservables. In order to do so, we estimate instrumental variable regressions. Given that the receipt of a research subsidy might depend on different criteria than the receipt of development subsidies, we constructed separate instruments for either one type of treatment.

We instrument the receipt of a research grant by two variables, namely the mean number of supported research projects by industry, size class and year and a variable capturing whether

the firm was previously engaged in collaboration that aimed at knowledge transfer. The rationale behind the former is that the more research projects supported within a certain industry and size class, the higher the likelihood that a firm i within this industry and size class may receive a grant. However, R&D intensity of firm i is not affected by the sector and size averages of this type of grant. The rationale behind the second variable is that firms engaging in collaboration which the aim of knowledge transfer may be more inclined to build on the knowledge acquired through this collaboration by engaging further into research in order to implement the knowledge into its own research projects in the future. As a consequence, the likelihood of applying (and hence receiving) a grant might be higher for these firms.

We instrument the receipt of a development grant by three variables. The first is the mean number of supported development projects by industry, size class, and year. The rationale behind this instrument is the same as the one presented for the research grants. In addition, we use previously supported development projects (three-year-lag) as a measure for experience with the funding scheme and the type of project. Third, we use collaboration with suppliers by year and type of ownership structure (i.e. is it a domestic firm or foreign owned firm), as both these characteristics might drive the selection into applying as well as into receiving a development grant. All five instrumental variables pass the standard criteria of relevance and exogeneity. The results from the two-stage least squares regressions are presented in Table 7. As can be gathered from the subsidy coefficients, our previous conclusions hold. The direct effect of a research grant is positive and significant, and larger than the direct effect of a development grant on development spending. In line with our previous findings, we find that the cross effect from D to R is larger than the direct effect from D to D.

Table 7: Instrumental variable regressions, N=4,442

	Direct effects		Cross effects	
Treatment:	Research grant	Development grant	Research grant	Development grant
Outcome variable:	<i>net research intensity</i>	<i>net development intensity</i>	<i>net development intensity</i>	<i>net research intensity</i>
	Model 1	Model 2	Model 3	Model 4
ln(research grant+1)	0.488 *** (0.108)			0.563 *** (0.171)
ln(development grant+1)		0.347 *** (0.084)	0.443 *** (0.058)	
R&D Collaboration	1.326 *** (0.112)	0.998 *** (0.121)	1.277 *** (0.108)	0.993 *** (0.125)
Patent stock/employee	0.953 * (0.498)	1.769 *** (0.571)	1.233 ** (0.508)	1.41 ** (0.609)
Foreign Parent	0.151 (0.171)	0.314 * (0.177)	0.212 (0.169)	0.28 (0.175)
ln(employees)	0.457 *** (0.161)	0.413 ** (0.162)	0.469 *** (0.160)	0.404 ** (0.157)
ln(employees) ²	0.02 (0.020)	0.035 * (0.021)	0.017 (0.020)	0.035 * (0.020)
ln(capital intensity)	0.164 *** (0.051)	0.004 (0.056)	0.174 *** (0.050)	-0.007 (0.055)
ln(age)	-0.229 (0.308)	-0.236 (0.338)	-0.167 (0.298)	-0.255 (0.327)
ln(age) ²	0.012 (0.058)	0.037 (0.063)	0.003 (0.056)	0.042 (0.061)
Constant	1.767 *** (0.505)	1.074 * (0.550)	1.673 *** (0.491)	1.046 ** (0.527)
F-test of excluded instruments	20.13 ***	23.24 ***	23.24 ***	20.13 ***
Hansen J overidentification test	0.1203	0.123	0.339	1.88
Joint significance of year dummies chi ² (9)	144.49 ***	70.73 ***	122.67 ***	100.14 ***
Joint significance of industry dummies chi ² (15)	109.93 ***	103.08 ***	108.2 ***	69.93 ***

Note: Standard errors are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%).

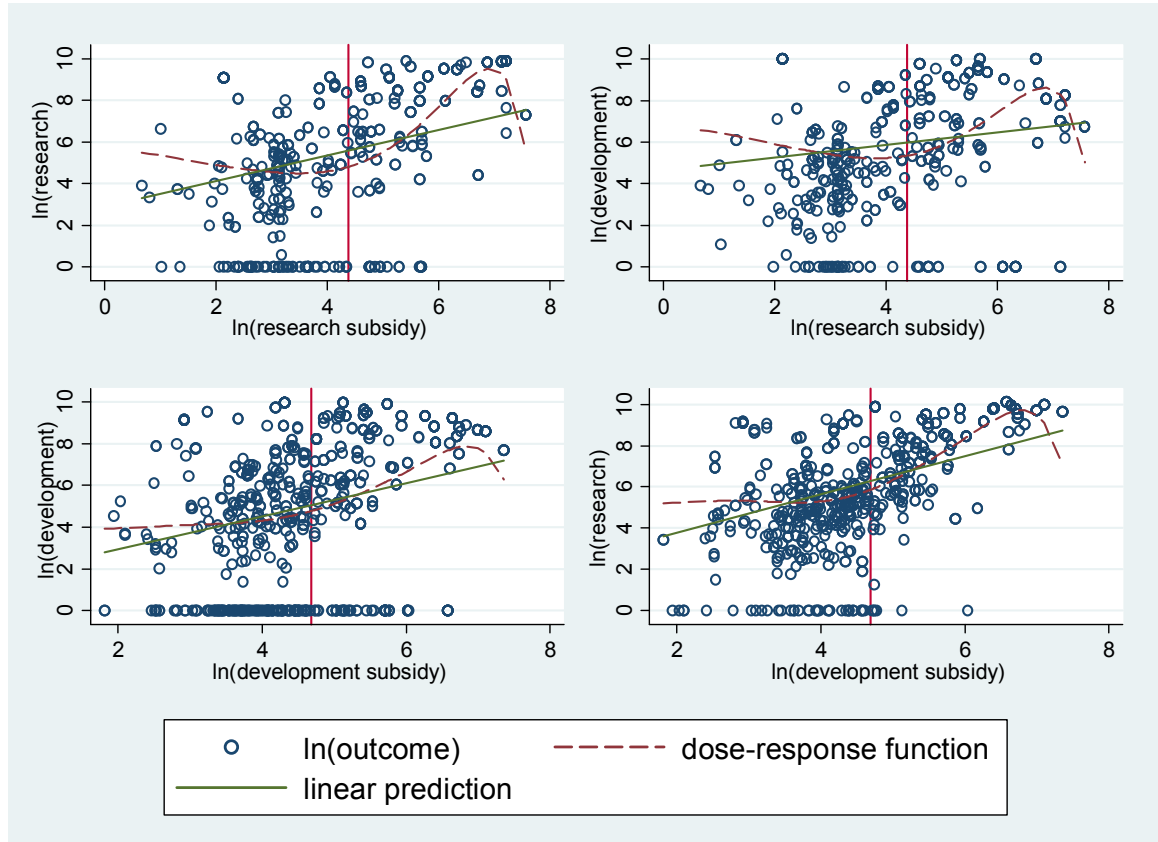
5.3.The dose response function (DRF) results

While the matching analysis allowed us to conclude that on average, the treatment effect is positive, the dose response function allows us to see whether the size of the subsidy matters in terms of net investment. The estimated DRF on expected net expenditures by level of treatment is shown in Figure 3. The subsidy amounts as well as the outcome variables are in logs so that the slope of the DRF is the elasticity of R and D spending with respect to the subsidy. On the left hand side, the graphs show the direct effects and on the right hand sides the cross effects.

For research grants, increasing the treatment level corresponds to lower levels of expected research investments for the first third of the treatment distribution. From that threshold onwards, an additional unit of the subsidy leads to a higher level of net investment. Only for the very high treatment levels, the relationship inverses again. As can be gathered from the graphs, the DRFs based on research grants as treatment show quite comparable patterns for the direct and cross effect, the latter being slightly flatter. This was to be expected given that we saw in the previous section that on average, the impact of a research grant is similar for R and for D expenditures. In both cases, the linear model would have predicted a positive relationship for all values of the treatment, while the DRF suggest that the positive effects prevail mostly in the area of larger subsidy amounts.

For development, the elasticity is low for grants smaller than the mean, but increases afterwards. Again, cross and direct effects follow a similar pattern. In all four cases, at the mean value of the subsidy amounts (vertical line), the elasticity is positive, meaning that an increase in the subsidy amount is associated with an increase in net spending. Overall, the dose response analysis seems to suggest an effective minimum subsidy amount and that – as long as the dose is not too large – an increase in the subsidy amount does translate into additional net spending by the recipient firms.

Figure 3: Estimated dose-response functions (direct and cross scheme)



5.4. Heterogeneity in the treatment effect

Not all firms may respond to the receipt of a subsidy in the same way. Table 8 shows the share of negative individual treatment effects, the share of positives and the share of treatment effects equal to zero. Given the considerable variation in the individual treatment effect, it is interesting to look at which firm attributes may impact the size of the treatment effects. Firms may be more likely to increase their investments once additional financing becomes available if they had put projects on the shelf due to a lack of financing. Since especially young small and medium sized firms may face financing constraints leading to shelved projects (e.g. Czarnitzki and Hottenrott 2011a; Cincera et al. 2014), one may expect a larger average treatment effect for these firms.

We estimate correlations between firm age and firm size and the direct and cross effects using OLS. We consider a firm to be young if it has been founded less than 7 years ago and small if it

employees 50 or fewer employees. A firm is of medium size if it has more than 50 but less than 250 employees. We are also interested in the interaction effect between small and young. We control for industry affiliation and the (annualized) grant size. The estimation equation is:

$$\begin{aligned} \alpha_i^{TT} = & \beta_0 + \beta_1 \ln(\text{grant amount})_i + \beta_2(\text{young}) + \beta_3(\text{small}) + \beta_4(\text{young} \times \text{small}) \\ & + \beta_5(\text{medium}) + \sum_{i=6}^{19} \beta(\text{ind}_i) + \varepsilon, \end{aligned} \quad (12)$$

Table 9 summarizes the results. For research grants, grant size positively affects the size of the direct treatment effect, but the effect is not particularly strong at the mean as the DRF analysis already suggested. Medium sized firms have a direct effect of research grants on research intensity that is about 7% larger than that of larger firms. While we do not find any significant effects for firm age, we find that young and small firms show a significant higher cross effect from R to D (22.3%). These results suggest that research grants facilitate additional development spending in these firms. For development grants, we find none of the firm characteristics to explain the direct treatment effect. For the cross effect on research, however, we find again that medium sized firms are associated with significantly higher cross effects, about 6% higher on average.

Table 8: Heterogeneity of direct and cross effects

	Research grant N= 198		Development grant N=319	
	<i>direct effect</i>	<i>cross- effect</i>	<i>direct effect</i>	<i>cross- effect</i>
Mean	0.031	0.038	0.014	0.055
Median	0.000	0.003	0.000	0.008
% <0	43.430	38.890	44.514	33.229
% = 0	6.060	3.530	9.404	3.135
% >0	50.510	57.580	46.082	63.636

Table 9: OLS regressions on the impact of size and age on the individual treatment effect α_i^{TT}

treatment	Research grant		Development grant	
dependent variable	α_i (net research intensity)	α_i (net development intensity)	α_i (net development intensity)	α_i (net research intensity)
<i>grant amount (annualized)</i>	0.030* (0.015)	0.003 (0.011)	-0.008 (0.011)	-0.002 (0.019)
<i>young</i>	-0.046 (0.074)	-0.005 (0.069)	0.033 (0.028)	-0.039 (0.034)
<i>small</i>	0.017 (0.038)	-0.010 (0.027)	-0.014 (0.011)	0.034 (0.027)
<i>young X small</i>	0.017 (0.098)	0.223*** (0.079)	-0.047 (0.053)	0.039 (0.087)
<i>medium</i>	0.069** (0.034)	0.028 (0.027)	0.011 (0.014)	0.060** (0.024)
<i>N</i>	198	198	319	319
<i>Joint sign. of industries</i>	1.84**	1.12	0.98	1.96**
<i>Overall significance</i>	2.42***	3.59***	1.44**	1.95**

Note: standard errors are robust. 13 industry dummies included.

6. Conclusions

This study analyzes how subsidies for research and development affect the net investment levels for these activities. Studying a data set with information on the grants and their recipients, we first find that public grants increase net R&D spending, on average, thus allowing us to reject the hypotheses of total as well as partial crowding out. Our findings refine previous insights by showing that research grants yield a higher average additionality than development grants. Second, we find that research and development subsidies not only trigger direct but also cross effects. While we find that development subsidies have a relative small direct effect on net development expenditures, they stimulate research expenditures. Research subsidies on the other hand spur own research as well as development, and this to a similar extent.

These results point to two phenomena. On the one hand, the direct effect may be larger for research grants, because research investments are more uncertain, more risky, more costly to finance and their results may be more difficult to appropriate. If firms for these reasons do not pursue research projects in absence of a subsidy, they may do so if a significant share is covered by a grant. For development projects, the market failures are less severe and a subsidy may therefore not have the same “additionality power”. The significant cross-effect from a development grant on research activities may, however, point to the fact that the additional funding facilitates additional research project by allowing the firm’s budget to shift from development to the more constrained research activities. The complementarity between research and development may explain the cross-effect that we observe from research grants on development activities. If a research subsidy facilitates additional research, this may also enable the firm to further pursue their product or process development at a larger scale. Analyzing the heterogeneity in the individual firm treatment effects shows that this cross effect is especially high for young and small firms.

Based on these findings, we can conclude that even though both subsidy schemes affect both parts of the R&D process, targeting subsidies to the research and development stage increased the overall amount of R&D invested in the economy. We further find that the dose matters: as long as the grant size is not excessive, larger doses generate higher additionality effects, both direct and cross-scheme.

Based on these findings, a major policy implication seems to be that specific schemes that take into account the peculiarities of the different components of the R&D process may increase efficiency of public co-funding programs. The results also encourage supporting projects in the early stages of R&D activities. These results should raise policy makers' awareness that development subsidies may have an effect on the type of activity that is relatively more likely to be affected by market failure. Supporting research projects in young and small firms may not only yield direct effects on the firms' research intensities, but also translate into additional development projects.

We strongly encourage further research on the efficacy of policy schemes in different environments in order to assess the generalizability of the insights gained in this study.

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Appendices

Appendix 1: Detailed Matching Protocol

Table A.1: The matching protocol¹¹

Step 1	Specify and estimate a probit model to obtain the propensity score $\hat{P}(X)$.
Step 2	Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. This step is also performed for other covariates that are possibly used in addition to the propensity score as matching arguments. In our case, industry classification and year for instance. This variant is called hybrid matching (see Lechner, 1998). Furthermore, for the case of development grants, we use firm size as an additional criteria.
Step 3	Choose one observation from the subsample of treated firms and delete it from that pool.
Step 4	<p>Calculate the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. $MD_{ij} = (Z_j - Z_i)' \Omega^{-1} (Z_j - Z_i)$</p> <p>where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls.</p> <p>We use caliper matching, first introduced by Cochran and Rubin (1973). The intuition of caliper matching is to avoid “bad” matches (those for which the value of the matching argument Z_j is far from Z_i) by imposing a threshold of the maximum distance allowed between the treated and the control group. That is, a match for firm i is only chosen if $\ Z_j - Z_i\ < \varepsilon$, where ε is a pre-specified tolerance.</p>
Step 5	Select the observation with the minimum distance from the remaining control group. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.) If the control group is empty after applying the caliper threshold, the treated firm is dropped from the sample and is not taken into account in the evaluation.
Step 6	Repeat steps 3 to 5 for all observations on subsidized firms.
Step 7	Using the matched comparison group, the average effect on the treated can thus be calculated as the mean difference of the matched samples:
	$\hat{\alpha}_{TT} = \frac{1}{n^T} \left(\sum_i Y_i^T - \sum_i \widehat{Y}_i^C \right)$ <p>with \widehat{Y}_i^C being the counterfactual for i and n^T is the sample size (of treated firms).</p>
Step 8	As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t -statistic on mean differences is biased, because it does not take the appearance of repeated observations into account. Therefore, we have to correct the standard errors in order to draw conclusions on statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors.

¹¹ The matching protocol follows Gerfin and Lechner (2002).

Appendix 2: Industry and size class distribution

Table A.2: Industry distribution

Industr	NACE (rev. 2008)	Description	Frequenc	%
1	10, 11, 12	Food and Tobacco	365	8.22
2	13, 14, 15	Textiles, Clothing and Leather	261	5.88
3	16, 31	Wood and Furniture	113	2.54
4	17, 18	Paper	104	2.34
5	19, 20	Chemicals	330	7.43
6	21	Pharmaceuticals	81	1.82
7	22	Rubber and Plastic	201	4.52
8	24, 25, 33	Metal	329	7.41
9	27, 28	Machines and Equipment	579	13.03
10	26	ICT	247	5.56
11	29, 30	Transport	114	2.57
12	41	Building and Construction	92	2.07
13	1, 5, 23, 37, 35, 32	Miscellaneous Industries	280	6.30
14	45, 46, 47, 49, 55, 58	Commerce and Transport	291	6.55
15	59, 64, 68, 69, 71 -	Other Services	607	13.67
16	61, 62	Software Development and Communication	448	10.09
			4,442	100.00

Table A.3: Firm size classes

Size	definition	Variable name	Frequency	%
1	< 20 empl.	Tiny	1,260	28.37
2	≥ 20 & < 50	Small	1,053	23.71
3	≥ 50 & < 100	Medium small	610	13.73
4	≥ 100 & < 250	Medium	720	16.21
5	≥ 250	Large	799	17.99
			4,442	100.00

Appendix 3: Robustness check: Additionality for a different distribution of the mixed subsidy scheme

Table A.4: Matching results (only outcome variables are presented) (33.3% of the mixed scheme is deducted from research expenditures, 66.6% of development expenditures)

	Outcome variables		
	<i>Net R&D intensity</i>	<i>Net Research intensity</i>	<i>Net Development intensity</i>
Treatment			
Any subsidy	0.049***	0.037***	0.012*
Research subsidy	0.070***	0.029**	0.041***
Development subsidy	0.047***	0.041***	0.006

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Only outcome variables are presented as control variables are all balanced after the matching.

Table A.5: Matching results (only outcome variables are presented) (33.3% of the mixed scheme is deducted from development expenditures, 66.6% of research expenditures)

	Outcome variables		
	<i>Net R&D intensity</i>	<i>Net Research intensity</i>	<i>Net Development intensity</i>
Treatment			
Any subsidy	0.050***	0.037***	0.013**
Research subsidy	0.068***	0.026*	0.042***
Development subsidy	0.040**	0.038***	0.003

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Only outcome variables are presented as control variables are all balanced after the matching.

**FACULTY OF ECONOMICS AND BUSINESS
DEPARTMENT OF MANAGERIAL ECONOMICS, STRATEGY AND INNOVATION**

Naamsestraat 69 bus 3500
3000 LEUVEN, BELGIË
tel. + 32 16 32 67 00
fax + 32 16 32 67 32
info@econ.kuleuven.be
www.econ.kuleuven.be/MSI

